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Monterey, California

A NEURAL-NETWORK BASED BEHAVIORAL THEORY OF TANK COMMANDERS

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A Neural-Network Based Behavioral Theory of Tank Commanders*

Abstract

Based on the presumption that certain data observed in high-tech and fast changing battles do have some intrinsic richness to them that synthetic modelling fails to capture, we contend that data induction techniques can be successfully used to generalize combat behaviors. This paper reports the use of neural networks as a computer-based adaptive induction algorithm to understand and uncover ground combat behaviors. Experiments with neural networks using tank movement data from the National Training Center (NTC), Fort Irwin, demonstrate that a two-dimensional cognitive map of closely task organized units can be derived. The findings seem to confirm our behavioral theory that tank commanders (i) are mission-driven, (ii) act as an integral part of their platoon, (iii) perform sequential decision making to determine their next moves, and (iv) when isolated, extemporaneous behaviors may take precedence over normative group behavior. Once trained, a neural-network based model of closely task organized units can be used to predict the itinerary sequences of a tank given its initial geographic position. The findings of this study are being used to support the route determination process within the Single Exercise Analysis Station (SEAS) prototype of the Enhanced Combat Training Center Analysis and Training Methodology (ECATM) research. The goal of the ECATM project is to improve the performance of scenario generation for Janus(A).

Keywords: Combat modeling, Knowledge exploration, Inductive reasoning, Applied Artificial Intelligence, Neural Network, Cognitive Mapping

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1. Introduction

In a high-tech ground battle or battle exercise, it is expected that concepts of operations, weapons technology and fighting capabilities of both forces, terrain and weather conditions, individual and collective mental attitudes of engaging troops *do* influence troops' behavior – although with a varying degree of intensity. To emulate this complex reality, combat simulators such as the US Army's Janus(A) combat model are equipped with algorithms to represent warriors' behavior in *typical* combats. Assumably, these algorithms rely on parameters that symbolically represent universal constants of human behaviors, e.g., the proven fighting doctrines and techniques. Furthermore, to cover the various battle contexts that might arise, combat simulators also provide calibration mechanisms for adjusting simulation parameters (for example, see Zyda and Pratt, 1991; Culpepper, 1992, Branley, 1992). For such a calibration to be effective, it has to be performed by well-trained and experienced analysts. Such an exercise *analysis* is time-consuming, subject to human errors, and runs the risk of being incomplete (Tversky and Kahneman, 1974), thus reducing the prediction power of combat simulators.

To circumvent this problem, this paper seeks a *behavioral* rather than analytical representation of the tanks in a battle field. Particularly, and as an effort towards using machine learning techniques for analyzing actual combat behaviors, we propose a neural network (NN) algorithm to capture the actual selection of routes by tank commanders when confronted by perpetually novel and evolving combat situations. When the quality of the data permits, the proposed computer-based adaptive algorithm can next be used to predict the itinerary sequences of a tank given its first position.

The paper is organized as follows. Section 2 introduces a dynamic perspective of the route determination process. Sections 3 and 4 present neural networks as an alternate approach to model closely tasked organizations. Section 5 describes neural network methodology and experimental procedures. It then proposes a cognitive map as an internal representation of tank commanders' behaviors. Summary of findings and recommendations for future research are provided in Section 6.

2. A Behavioral Model of Closely Task Organized Units

All combat engagement should be the result of a well-defined mission (i.e., tactical goal expressed by mission statement) and a well-thought action plan (i.e., tactical actions). According to the U.S. Army doctrine (FM17-15, 1987), a tank commander should determine his route according to the following major principles:

1. Follow the route determined by the concept of operation;
2. Employ unit movement techniques and drills to balance speed with likelihood of enemy contact;
3. Use the terrain and natural or man-made cover and concealment to mask his weapon system from enemy observation.

It is expected that trained troops - while engaging in combat - should adhere as closely as possible to the concepts of engagement laid out by high-level command. However, actual combat behaviors might deviate from the planned ones, including significant departures from company commander's intent and execution plan. For example, tank commanders are trained that "what can be seen can be killed," so the use of cover and concealment is key to survival on the modern battlefield. When a tank is required to cross open areas, speed and overwatch techniques are used. Factors governing a tank commander's movement include his vehicle's position, route, enemy positions, and his vulnerability. It can be observed that in actual combat situations, tank commanders exhibit the following behaviors when they choose a route:

1. Tank commanders are mission- or goal-oriented. They seek to move as fast as their mission and battle conditions allow to their assigned destination. Drills are used to minimize command and control problems inherent in battle.

2. Tank commanders act as an integral part of their platoon. They are trained on movement techniques and drills which balance speed, use of terrain, and likelihood of enemy contact. They maintain visual contact with other tanks that belong to their platoon. As battle progresses, they adjust their position relative to those of the platoon.

3. Decisions pertaining to route adjustments are sequential. There is an implicit behavior to reject inconsistent moves that do not support the mission.

4. When all communications are lost, extemporaneous behaviors from isolated individual tankers may take precedence over normative group behavior.

As discussed earlier, we contend that route determination, more often than not, is a dynamic and real-time reasoning process with incomplete and quite possibly inexact information. As the battle unfolds, each time slice can be perceived by the engaging tank commander as a life-threatening crisis that forces him to re-evaluate his next movement. The quality of the sequential and dynamic route determination process depends on a large number of factors – particularly, his ability to make use of his knowledge and experience to quickly assess battle situations.

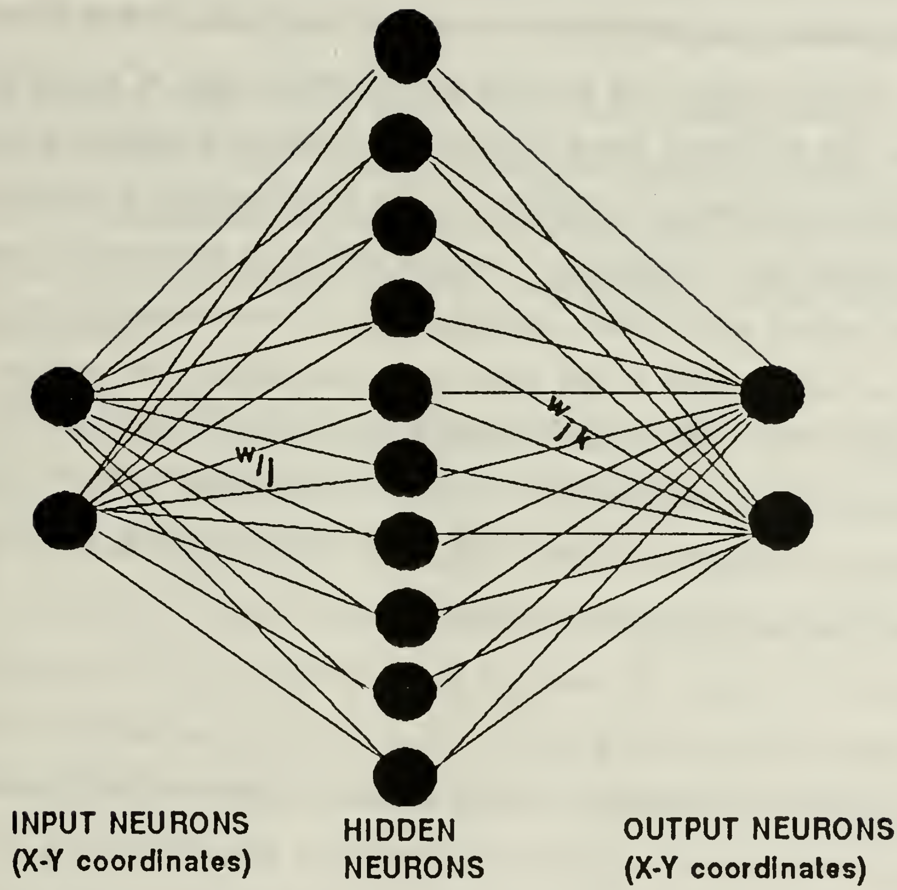
3. Route Determination Paradigms

3.1 Deductive and Inductive Approaches to Route Determination

As a decision problem, a closely tasked organization can be determined by using one of the following two paradigms. The deductive approach tries to explain phenomena in terms of causes and effects. All relevant factors that could lead to the construction of a route should be taken into consideration. Once all hypotheses are formulated and required data gathered, models will be used to predict tank movements. Conversely, the inductive approach conjectures that, in some complex situations such as the route determination process, it would be impossible to model all direct causal relationships due to incomplete, uncertain and dynamic information. To circumvent the difficulty in applying analytical reasoning using quantitative algorithms, the inductive approach hypothesizes that there is a lot to learn from those tanks that successfully make it through to their planned destination. It is believed that "lessons" can be learned by acquiring, processing and refining "knowledge" from actual routes of the mission-accomplished tanks. Hunt (1982) observes that humans possess a "natural" form of reasoning that works surprisingly well in uncertainty. Natural reasoning exploits experience and analogy to reach plausible conclusions. Patterns of a problem are analyzed and compared to previous experiences in an attempt to search for similar circumstances and comparable solutions - in form of "educated guesses". Advocates of this biological approach recognize a strong connection between the structure of the human brain and the ability to reason. The remaining part of this paper describes the use of an artificial neural network (NN) as an analog of the human brain.

3.2 A Brief Description of Neural Networks

A neural network is a system consisting of a number of simple, highly interconnected homogeneous processing units called neurons (see Figure 1). Each neuron is a simple computational device that continuously reacts to external inputs. This reactive behavior can be modeled by relatively simple mathematical functions (For a survey of mathematical functions for neural nets, see for example Hecht-Nielsen, 1988). Typically, a neuron receives input signals from other neurons, aggregates these signals based on an input function, and generates an output signal based on an output or transfer function. The interconnections between neurons is represented by a weighted directed graph, with nodes representing neurons, and links representing connections. The relative



Legend: w_{ij}, w_{jk} : connection weights

Figure 1. A Neural Network Architecture for Tank Routes

importance of the link between two neurons is measured by the weight assigned to that link. A crucial problem in training neural network is to determine a set of weights assigned to the connections that best map all input units to their corresponding output units. In other words, the learning process can be seen as a non-linear optimization problem that minimizes output differences. There are a number of algorithms that can be used to minimize output differences. The back propagation technique is presently the most popular one. Iteratively, it assigns weights to connections, computes the errors between outputs and real data, propagates these error information back, layer by layer, from the output units to the input units, and adjusts the weights until errors are minimized. The back propagation mechanism does not guarantee an optimal solution. However, various experiments reported by Rumelhart et al. (1986) and by other researchers (Maren et al., 1990; Freeman, 1991) suggest that the algorithm provides solutions that are close to the optimal ones.

4. A Neural Network Based Adaptive System for Route Determination

The purpose of this experiment is to develop and calibrate a learning algorithm for a platoon faced with tank movements with initially unknown and random consequences. We assume that the tank commander is able to maintain a high level of situational awareness to continuously adjust his route. However, he is facing a problem of iterated choice under varying degrees of uncertainty (i.e., fog of war). He chooses one of many feasible routes on a "trial" basis, observes the consequence(s) or benefit(s) of that move, and continuously adjusts the tank's direction and speed.

We propose a complex adaptive system for route determination for a tank based on the analysis of its platoon's behavior. The system is complex in that its behavior (i) is based on the dynamic movements of individual tanks that belong to a formation; (ii) exhibits many levels of aggregation and interaction, and (iii) is derived from actual route data without a detailed knowledge of how each route had been chosen. The system is also an homuncular one in that it learns only from the past experiences of its own platoon, and environmental factors – such as concepts of engagement, terrain and weather conditions, enemy powers, etc. – are somehow embedded in past performances.

Such an adaptive system usually operates far from a global optimum. However, actual data do have some intrinsic richness to them that synthetic modelling could not replicate. Also, it would be easier to capture behaviors that inherently embrace analytical reasoning than to synthetically model the reality that includes, among numerous other factors, human behaviors.

Furthermore, we believe that by observing victorious tanks that successfully made it to destination, sample patterns could be molded and memorized for later use. Learning from these patterns should provide faster and more sensible cues.

Figure 1 describes a simple structure of a neural network designed to learn and simulate the behavior of tank commanders of a platoon in combat. The network is defined by (i) the interconnection architecture between the processing elements – i.e., timely positions of different tanks of a platoon (ii) a transfer function that determines the processing rules, and (iii) learning laws that dictate changes in the relative importance of individual interconnections. Once the system is successfully trained such that it is able to represent the structure and dynamics of actual tank movements, it can be used to simulate/predict the route of a tank given its original geographic position.

5. An Experiment with the Neural Network Model for Route Determination

5.1 Data and Procedures

For the purpose of this experiment, the actual routes of eight tanks in a battle exercise conducted at the National Training Center, Ft. Irwin, were used to train the network model. The tanks were part of a company whose mission was to reach their destination located approximately 9 kilometers North-East of their initial positions. The platoons moved towards their goal expecting possible contact with the opposing force. All eight tanks achieved the goal.

To emulate the tank commanders' behavior, a neural net was constructed. It has 2 input nodes representing the geographic (latitude/longitude) coordinates of each of the 8 tanks; 2 output nodes representing the geographic coordinates of the subsequent position of a typically behaved platoon tank; and 10 hidden neurons impersonating the internal representation of the perceived environment by the tank commanders. Figure 2 plots the routes of the eight tanks. Each route is represented by forty-three coordinates taken at five minute intervals, beginning with the point of departure and finishing with the destination point.

The back propagation technique was used as the input/output transfer function to determine the relative importance of the interconnections between tank coordinates over time. The network was successful trained to 94% of the training facts after 202 passes, with a training tolerance of 0.1. As expected, the network could not be trained with no tolerance (i.e., training tolerance = 0), because of the noise (stochastic or other) depicted in the routes; i.e., in some portions of the routes, tanks seemed to move slightly to directions other than the intended one toward the planned destination. Figure 3 shows routes simulated by the trained network. The simulated routes retrace with a high level of accuracy the actual routes.

5.2 Testing of Tank Commanders' Behaviors

The successfully trained network could be used to simulate different tank movements given the original position. In this section, we attempt to relate the simulation results of our neural network to the combat behaviors of tank commanders presented in Section 2.

1. *Tank commanders are mission-oriented.* Simulated platoon routes do result in a standard asymptotic pattern converging towards the final destination.

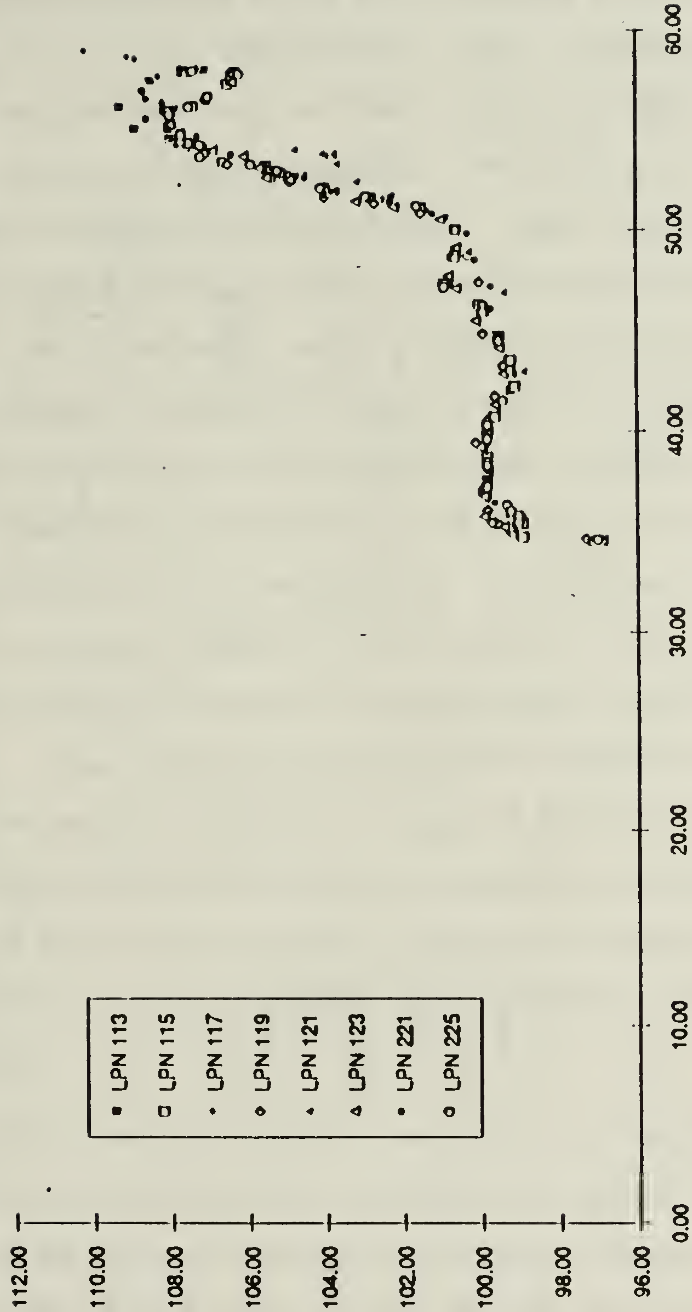


Figure 2. Actual Tank Routes

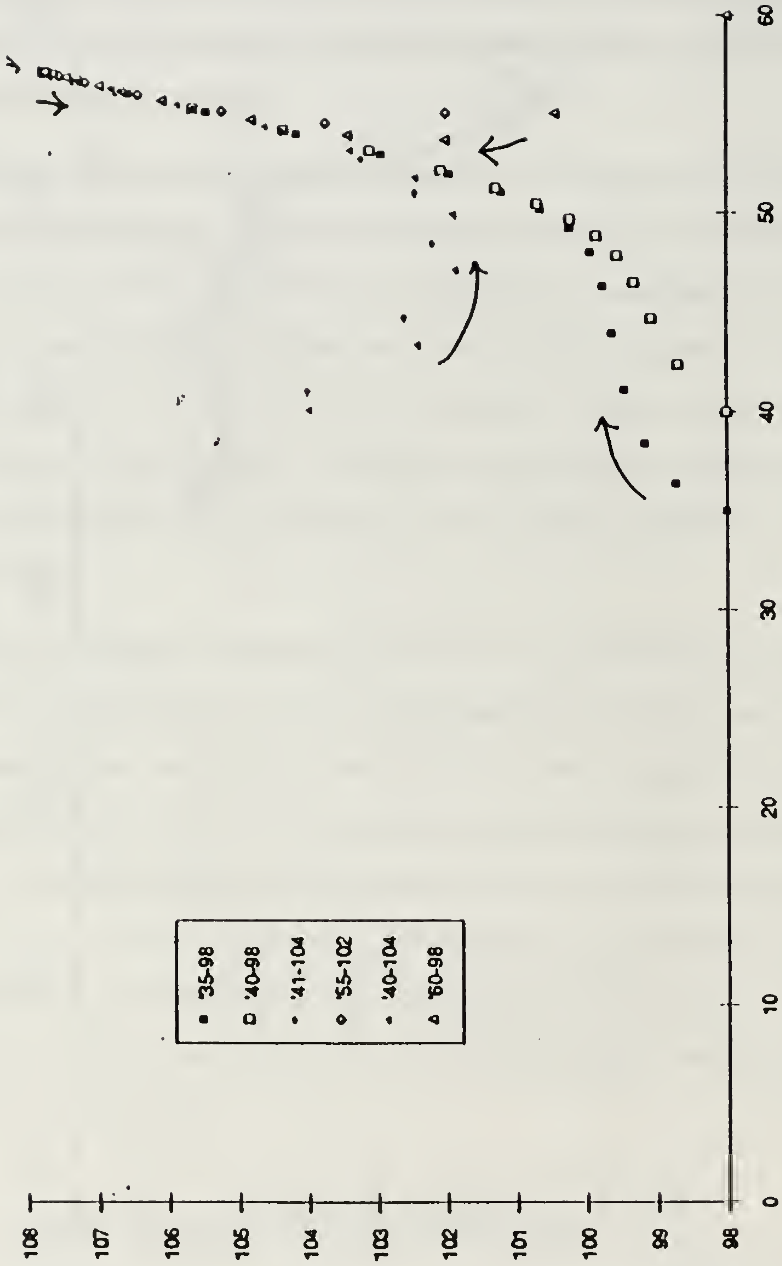


Figure 3. Simulated Routes using a Trained Neural Net

As illustrated in Figure 3, 7 simulated tanks were positioned at various starting points. The routes suggested by the trained network mimicked well the actual counterparts. For example, tanks 35-98 (i.e., with the initial position on the map at 35km on the East-West axis, and 98km on the North-South axis) and 40-98 started at the same positions of actual tanks. The simulation provided the routes *and* the relative speeds to reach destination. Tanks were expected to move quickly at the beginning of their mission, and then to slow down as enemy contact could occur in the central valley, and to gradually reach their target.

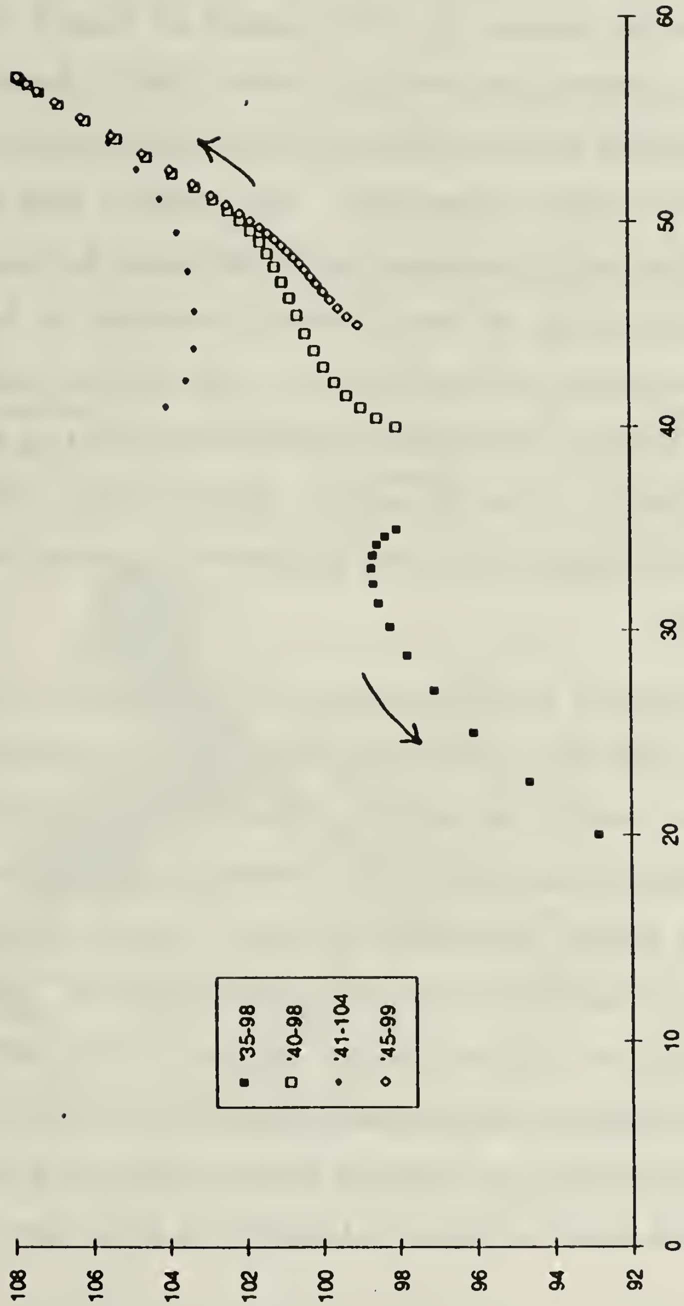
Of particular interest, we simulated the tanks positioned at locations different than the ones used to train the network, especially the one situated at the northern region of the destination zone (55-112). The trained network suggests a short route that leads directly to the intended goal. To further test the mission-driven behavior, we purposely initiated two tanks (40-104; 41-104) from a "no-go" terrain - even though we knew that, in practice, there would be no tanks at that hilly position. The trained network managed to guide them towards the goal area. More importantly, it seemed to recognized the terrain condition. Instead of going straight to the identified goal, the suggested route would take the tank quickly out of the "suspected obstacle" and guide it through the safe contour. Eventually, all tanks stopped once they reached the goal. This hints the stability of the goal state.

2. *Tank commanders consider themselves as an integral part of their platoon.* To test the effect of team coordination, we picked a tank positioned approximately 3 miles south of the rear end of the platoon positions. The tank apparently acted as it recognized that it did not belong to the platoon. It headed for another direction. Similar positions were tested and similar results were obtained. Psychologists who used the Hopfield network (an earlier neural network technique to mimic associative recall) have discovered the same phenomenon (See for example, Hecht-Nielson, 1989). They would argue that the neural net recognized that the tank was not in the vicinity of other tanks - a situation it had never

observed before –, thus decided to generate another goal for that "exotic" tank. Suggesting alternate goals is a innovative approach that learning systems could provide.

3. *Tank commanders perform sequential decision making.* The trained neural net simulated the route one five-minute step at a time. After each move, each re-trained itself, learned from its past, and decided on the next move. The trained net is feed forward. The output is then fed back as the next input, but no retraining occurs. (As can be seen in Figure 3, the trained neural net can "look farther ahead"; a similar phenomenon was discovered by Hutton and Sigillito, 1991). Seemingly, once the system discovered the goal, it tried to accomplish its mission while minimizing its cognitive effort. Wherever possible, fewer and faster steps were identified to reach the final target. Eventually, all of them conversed at the intended target.

4. *Tank commanders reject inconsistent movements.* In testing the trained network, we had no problem re-tracing the tanks that were stationed at their intended starting positions. The simulated routes were determined as expected. We were not sure, however, how to position the tanks to start at "unconventional" starting locations and interpret the respective routes suggested by the trained neural net. In particular, we wanted to train the neural net to recognize "no-go" terrain so that it can "penalize" all attempts to start a tank at an infeasible position. Note that this is a theoretical issue for, in reality, no analyst or company commander would assign tanks at impossible location. A set of feasible routes were artificially created to emulate the zone of "go" terrain and added to the original data set (Figure 4). As might be expected, the system was trained with a much lesser degree of confidence. In the simulation after training, the tanks seemed to wander around with much less determination than in the net trained with only real data.



Legend: Arrows indicate direction of simulated routes

Figure 4. Trained Network with Feasible Routes

5.3 A Two-Dimensional Cognitive Map of Closely Tasked Organizations

Cognition is the process by which external or sensory inputs are perceived, processed, stored, recovered, and used (e.g., Neisser, 1967). In this section, we attempt to synthesize the findings of our experiment by constructing a cognitive map used by tank commanders during combat engagement. The cognitive map provides a symbolic representation of how tank commanders see the battle (see 5.2), yet is capable of using this internal representation to solve dynamic problems at hand. The internal representation is a mixture of knowledge (i.e., that which is known to be true about something), and beliefs (i.e., that which is believed to be true) – a common phenomenon discovered in cognitive science (Konolidge, 1986; Hintikka, 1962). Figure 5 is a cognitive map of the tanks used in this experiment, presented on a two-dimensional geographical space.

The neural network learned that there was a *goal/mission* – better yet, a stable and purposeful one. Tanks that are seemingly not part of the mission should look for other goals (i.e., *alternate goals* in the map). Environmental factors are embedded in the way tanks moved. Tank movements and speed reflected the terrain and weather conditions, as well as enemy forces. Emulation of "known" routes displays a *habit formation* characterized by an exacting behavior with repeated exposure. Emulation of "unknown" routes suggests that new behavior can be *"learned"* to face with new contexts. The analysis of these confirmed and revealed behaviors could help discover *unapparent knowledge*. As an example, the suggested routes to reach the destination systematically showed a consistent detour suggesting a forbidden or no-go zone on the left-hand side.

5.4 Discussion

The experiment conducted in this paper suggests that a simple dynamic system could represent a complex reality such as tank commanders' behaviors in battlefield. For a *short-term, well-focused* decision problem such as the process of route determination, the data induction technique helps understand behaviors without requiring full

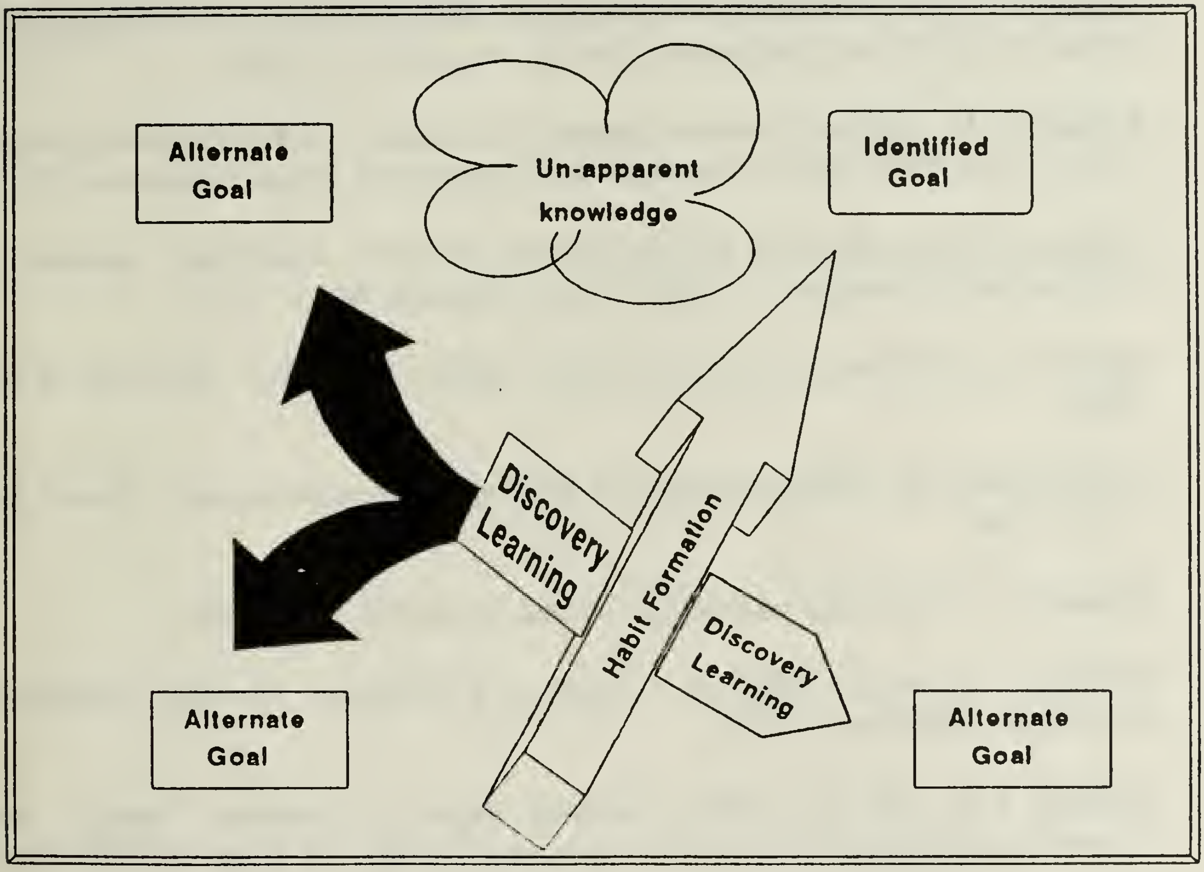


Figure 5. A Neural-Network Based Cognitive Map of Tank Commanders

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